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Modeling Financial Indicators of AI Agent Implementation: Optimizing Business Margin and Customer Service LTV

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ABSTRACT

The study is focused on the formation of an integrated financial model for the implementation of AI agents in customer service and the evaluation of their impact on operational efficiency, business margin, and customer LTV (Lifetime Value). The task appears simple. In fact, it is not. The relevance of the topic is explained by the fact that scientific approaches to assessing the economic effect of AI remain fragmented. Because of this, it is difficult to see a holistic picture of the relationship between costs, productivity, and customer behavior. In this work, attention is focused on the development of a model that combines operational indicators and behavioral characteristics within a single system for evaluating the financial results of an enterprise. The methodology is of a conceptual-analytical type with system and comparative analysis methods. Most similar studies are like that. But at the same time, the results of empirical studies from 2022–2026 are taken into account, in which the impact of AI agents on productivity, costs and customer behavior is quantitatively assessed. As part of this method, a synthesis of scientific positions was carried out and, on this basis, an analytical model of relationships between key financial indicators was built. Data matters. The obtained results show that the implementation of AI agents increases operational efficiency. This occurs through the automation of repetitive processes, the reduction of request processing time, and a decrease in variable costs. The effect of scale works. Increasing volumes without proportional growth in resources becomes a key factor in increasing business margins. At the same time, the improvement of customer experience, in particular through the personalization of interaction, is associated with the growth of retention rate and LTV. As a result, the model shows that ROI is formed under the influence of both operational and behavioral changes. It has also been established that the effectiveness of implementing AI agents depends on the context. Everything depends on the conditions. Decisive importance is given to the level of digital maturity of the enterprise, the type of customer scenarios, and the balance between automation and human involvement. The practical value lies in the possibility of using this model to justify investments in AI solutions, evaluate their financial efficiency, and forecast long-term business results.

KEYWORDS

AI agents, ROI of AI agent implementation, operational efficiency with AI agents, AI economics of business profitability, customer LTV (Lifetime Value), financial model of AI agent implementation.

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СОЦІАЛЬНИЙ РОЗВИТОК:
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Моделювання фінансових показників впровадження AI-агентів: оптимізація маржинальності бізнесу та LTV клієнтського сервісу

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СТАТТЯ

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АНОТАЦІЯ

Дослідження зосереджено на розробці інтегрованої фінансової моделі для впровадження агентів ШІ в обслуговування клієнтів, з особливою увагою до оцінки їхнього впливу на час відгуку, структуру операційних витрат, бізнес-рентабельність та цінність життя клієнта (LTV). Хоча на перший погляд завдання може здатися простим, його реалізація ускладнюється методологічною фрагментацією існуючих підходів до оцінки економічних ефектів ШІ. Сучасні дослідження, як правило, зосереджуються на ізольованих вимірах – витратах, продуктивності або поведінці клієнтів – що обмежує можливості фіксації взаємозалежності між цими змінними. Це дослідження усуває цю прогалину, пропонуючи підхід, який інтегрує операційні та поведінкові показники в єдину аналітичну структуру для оцінки фінансових показників фірми. Методологічною основою дослідження є концептуально-аналітичний підхід, підкріплений системним та порівняльним аналізом. Крім того, дослідження включає результати емпіричних досліджень, проведених між 2022 та 2026 роками, які надають кількісні докази впливу агентів ШІ на продуктивність, витрати та поведінку клієнтів. На основі синтезу цих результатів розроблено аналітичну модель взаємозв'язків між ключовими фінансовими показниками. Результати вказують на вимірне підвищення операційної ефективності після впровадження агентів ШІ. Це покращення в першу чергу зумовлене автоматизацією повторюваних процесів, скороченням часу реагування та зниженням змінних витрат на кожну взаємодію з послугою. Значну роль відіграє ефект масштабування, який дозволяє фірмам збільшувати обсяги послуг без пропорційного зростання ресурсів, тим самим сприяючи вищій маржі. Водночас спостерігаються зміни в поведінці: покращена персоналізація та узгодженість послуг позитивно впливають на утримання клієнтів та LTV (цільову вартість обслуговування). Як результат, показано, що ROI виникає в результаті комбінованого ефекту операційних покращень та змін у поведінці. Водночас ефективність впровадження агентів ШІ залежить від контексту. Ключові детермінанти включають рівень цифрової зрілості фірми, характер сценаріїв взаємодії з клієнтами та баланс між автоматизованими та людськими елементами у наданні послуг. Практична цінність запропонованої моделі полягає в її застосовності для обґрунтування інвестицій у рішення ШІ, оцінки їх фінансових показників та прогнозування довгострокових бізнес-результатів.

КЛЮЧОВІ СЛОВА

AI-агенти, ROI впровадження AI-агентів, операційна ефективність з AI-агентами, AI-економіка маржинальності бізнесу, LTV (Lifetime Value) клієнта, фінансова модель впровадження AI-агентів.

1. Introduction

The digital transformation of business has been developing chaotically in recent years. It is increasingly moving away from gradual changes and moving to a deeper restructuring of how the company interacts with the client. A different logic appears. The proliferation of generative AI and agent-based systems has actually forced a revision of the basic operating models in customer service. If earlier contact centres were based on human resources and grew along with costs, almost step by step, now the situation looks different. AI agents take over a large part of the requests and do so without a corresponding increase in costs. The economy begins to act according to a different logic. This can be seen in practice. As a result, a new service model is formed, where costs, response speed, and quality of interaction with the client are correlated in a different way.

At the same time, the very role of customer service is changing. It no longer looks secondary. It's more than sales support. The service is gradually becoming a factor that determines whether the client stays, returns again, and what value it will bring over time. The parts begin to have weight. Interaction is perceived more subtly, and it is in these nuances that the general attitude towards the company is formed. Providing AI-powered solutions as part of customer experience and, in particular, personalization, can increase satisfaction and build sustainable behaviour patterns. And, ultimately, this translates into an increase in the long-term value of the customer. The effect accumulates. In this sense, automation is not limited to improving the efficiency of operations.

Despite the growing number of studies, the scientific literature in this area still looks scattered. There are many observations. Integrity is lacking. Part of the work is focused on productivity and process automation. Others rely on customer behaviour, churn, or the quality of their experience. This is rarely combined in one approach. At the same time, there is no integrated financial model that would simultaneously take into account operating costs, customer behavioural parameters and their impact on key business results. This is exactly what is missing. Such methodological disunity complicates the quantification of the effectiveness of investments in AI-based solutions and narrows the opportunities for informed management decisions.

The purpose of the study is to develop an integrated financial model for the implementation of AI agents in customer service, which allows explaining the relationship between changes in the cost structure, operational efficiency, and behavioural characteristics of customers. The proposed approach involves a simultaneous analysis of service costs, customer retention rates, and LTV dynamics, which makes it possible to assess the impact of automation on business margins in the medium and long term.

2. Literature Review

The problem of using artificial intelligence agents in customer service and their impact on the financial results of companies is currently actively developed in the scientific literature and is accompanied by a significant amount of empirical and theoretical research. In particular, I. M. Enholm et al., as well as B. Y. Kassa and C. Ledro emphasize the transformative potential of AI for business processes and financial results of enterprises [8; 11; 12]. At the same time, approaches to its analysis remain heterogeneous and often contradictory, which is due to the difficulty of simultaneously taking into account the operational, behavioral, and financial effects of AI implementation. It is advisable to conditionally group the existing studies into three main directions. The first is related to the assessment of the business value of artificial intelligence through the prism of operational efficiency and productivity, which is reflected in the works of E. Brynjolfsson and L. Fang [5; 9; 11]. The second focuses on the impact of AI solutions on customer experience, satisfaction, and behavioural responses of consumers, which is studied by L. M. Aguiar-Costa, Y. Chen, and K. Hardcastle [1; 7; 10]. The third direction is focused on the analysis of financial indicators, in particular, the long-term value of the client (LTV), which is reflected in the works of N. Ali, H. Chen and C. Ledro [3; 6; 12].

The first direction is related to the study of the impact of AI on productivity and cost structure. I. M. Enholm et al. [8] systematize approaches to assessing the business value of artificial intelligence, emphasizing its ability to transform operational processes and form new sources of competitive advantage. A similar logic is developed by B. Y. Kassa and E. K. Worku [11], who prove that the financial effect of AI implementation is mediated by increased productivity, which, in turn, leads to lower costs.

Empirical results also confirm that the use of generative AI in customer service can significantly increase employee productivity and service quality, especially in the case of performing typical operations [5]. At the same time, these approaches focus mainly on the internal efficiency of the enterprise, leaving out the behavioural aspects of interaction with customers.

The second area of research focuses on the transformation of customer experience. Y. Chen and C. Prentice [7] analyse the relationship between the use of AI technologies and the quality of customer experience, emphasizing the role of personalization in building customer loyalty. C. Ledro et al. [12] consider the implementation of AI in CRM as part of a comprehensive transformation of the customer interaction system. At the same time, as noted by S. Rana and colleagues [17], excessive automation can lead to a decrease in the quality-of-service perception. Additional research confirms that personalized AI solutions create a more positive customer experience and increase user engagement, but the effect depends on customer perception of the technology [10]. Thus, the effect of AI in this plane turns out to be ambiguous and depends on the balance between manufacturability and human interaction.

The third direction is related to the financial assessment of the customer base and forecasting its long-term value. N. Ali and O. S. Shabn [3] consider CLV as a key indicator of strategic management, reflecting the cost-effectiveness of interaction with customers. H. Chen et al. [6] propose to use machine learning algorithms to predict LTV, which can improve the accuracy of management decisions.

Special attention in the literature is paid to the limitation of the use of AI. A. Yao and colleagues [18] investigate the phenomenon of negative perception of automation by consumers, which can neutralize the expected economic effect. The financial results of AI adoption are determined not only by operational efficiency but also by customer behavioural responses.

The problem of using artificial intelligence agents in customer service and their impact on the financial results of companies is currently actively developed in the scientific literature and is accompanied by a significant amount of empirical and theoretical research. It provokes active scientific discussions and forms different approaches to the interpretation of the results obtained. At the same time, approaches to its analysis remain different from each other and often contradictory, which is associated with the complexity of assessing the integrated effect of AI implementation in business processes [8; 12]. The existing research can be divided into three areas. The first is to assess the business value of AI through operational efficiency. The second is the impact on customer experience. The third is based on financial indicators, in particular on the dynamics of LTV.

3. Problem Statement

The purpose of this study is to form a financial model for the implementation of AI agents, which explains the impact of customer service automation on operational efficiency, business margin, and LTV (Lifetime Value) of the client.

4. Methods and Materials

The methodological logic of this study is formed at the intersection of analytical generalization and applied economic analysis. We deliberately did not limit ourselves to one approach, since the very nature of the impact of AI agents on customer service turns out to be multidimensional and is not limited to operational or financial indicators. Therefore, it was based on working with various types of sources – scientific publications, analytical reports, and empirical studies that record real changes in business processes after the implementation of AI solutions.

In the process of analysis, attention was focused not so much on individual indicators as on their interconnections. Gradually, a certain structure emerged: the costs of processing requests, the behavioral characteristics of customers, in particular the level of their retention, as well as the dynamics of long-term value (LTV) began to be considered as interrelated elements of one system. Generalization of the available approaches made it possible not only to compare these indicators, but also to try to see how changes in one of them affect the others.

5. Results and Discussion

5.1. The impact of AI agents on business operational efficiency

The introduction of AI agents in customer service is accompanied by a systemic transformation of the operating model, where the automation of routine interactions and the redistribution of the load between systems and personnel play a key role. Unlike the traditional model, in which the volume of service directly depends on the number of operators, the use of AI allows you to scale the processing of requests without a proportional increase in costs [5].

Empirical evidence shows that the integration of AI assistants increases customer support productivity by an average of 14–15%, as measured by the number of resolved requests per unit of time, as shown in research by Erik Brynjolfsson and colleagues [5]. At the same time, the results of field experiments by L. Fang et al. indicate that the introduction of generative artificial intelligence has a statistically significant positive impact on the financial results of enterprises, in particular, providing sales growth in the range from 0% to 16.3%, depending on the context of use and the level of integration of the technology [9]. Similar conclusions were also obtained by K. Marcineková and colleagues [13], who emphasize that most typical operations go into automated mode, while employees focus on complex cases.

Operational efficiency indicators change primarily in three dimensions: response time, system throughput, and request processing cost. The experience of implementing AI solutions demonstrates a reduction in the Average Handling Time by about 30–39% during the first months of using AI agents. At the same time, the number of requests that can be processed without involving additional resources is growing, which creates the effect of operational scaling [5].

To summarize the impact of AI agents on key indicators, an analytical table was formed based on scientific research.

Table 1. Changes in operational performance under the influence of AI agents

Indicator	Before the introduction of AI	After the implementation of AI
Proportion of auto-processed requests	0–10%	up to 70%
Average Request Processing Time (AHT)	Basic level	↓ by 30–39%
Performance (requests/hour)	Basic level	↑ by ~14–15%
Burden on operators	100%	↓ by 5–12%

Source: Systematized by the authors based on [2; 5; 9; 13].

As follows from the data given in Table 1, the impact of AI agents on operational activities is complex and manifests itself simultaneously in several interrelated dimensions. First of all, there is a significant increase in the share of automatically processed requests — from the basic 0-10% to a level that can reach 70% in practical scenarios of using chatbots. This indicator reflects the general trend of automation of standard operations, while the results of L. Fang et al. confirm the financial effect of AI implementation in the form of sales growth [9]. At the same time, there is a reduction in average case processing time (AHT) by 30–39%, reflecting an increase in response speed and optimization of standard operating procedures. Changes are not limited to time parameters. An increase in productivity of approximately 14–15% correlates with the results of research by E. Brynjolfsson and colleagues [5], which demonstrate an increase in the efficiency of performing typical tasks in a generative AI environment. At the same time, the reduction of the workload on operators, although it looks moderate in quantitative terms (5-12%), has a qualitatively different effect: there is a redistribution of working time.

The trajectory of performance changes after the introduction of AI agents is not equal. At the initial stage, the effect manifests itself most quickly – primarily due to the automation of typical, repetitive operations. It is here that the largest increase is recorded. Over time, the dynamics slows down. Productivity is no longer growing at this rate, but is gradually reaching a more stable level. As a result, the initial "jump" is replaced by the consolidation phase: the effect does not disappear, but stabilizes and becomes part of the operating model.

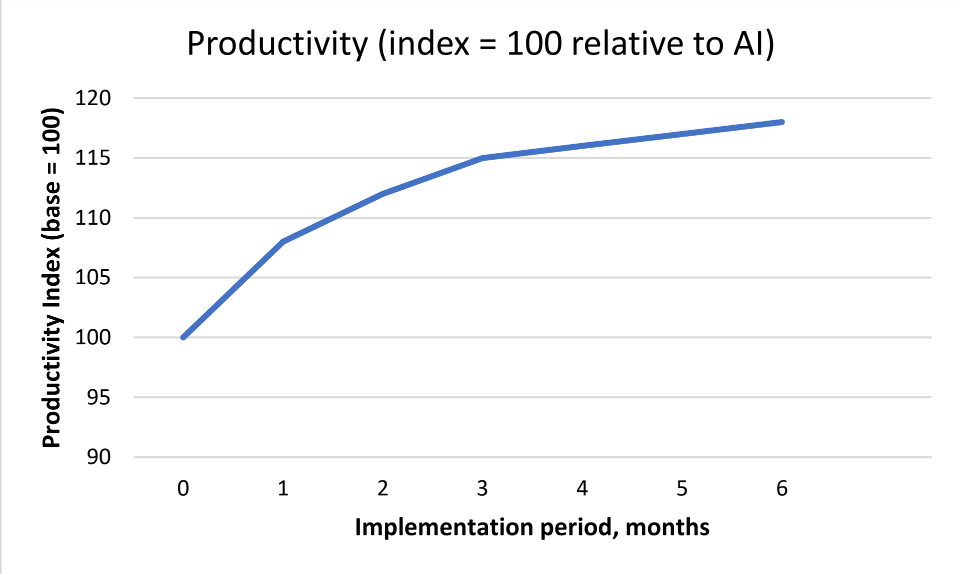

Fig. 1. Dynamics of customer service performance after the implementation of AI agents

Source: Built by the authors based on [5; 9].

As shown in Figure 1, performance dynamics after the introduction of AI agents are uneven and go through several successive phases. At the initial stage, a sharp increase in the indicator is recorded, which is explained by the automation of standard and repetitive operations, which is confirmed by the results of E. Brynjolfsson and colleagues [5]. In the future, the growth rate will gradually slow down, which is associated with the saturation effect: further productivity gains can no longer be provided only by the automation of typical tasks. Similar conclusions were obtained in the studies of L. Fang et al. [9], which emphasize that in later stages, efficiency depends on deeper integration of AI into business processes. As a result, the primary effect of transformation passes into the stabilization phase, where the achieved level of productivity is consolidated and becomes part of the operating model of the enterprise.

A separate role is played by the standardization of interaction with customers. AI agents provide stable quality of responses and minimize the impact of the human factor, which reduces the variability of results and increases the predictability of the service [2; 13]. The linguistic characteristics of interaction, which determine the perception of the quality of service by customers, are of particular importance. A study by S. Brunswicker et al. demonstrates that the style of AI agents' responses, in particular the balance between rational structuring and empathy, directly affects the level of user trust and the effectiveness of tasks in the process of interaction [4]. Thus, the language component of interaction acts as an additional factor in increasing the operational efficiency of customer service.

As a result, the basis for changes at the financial level is formed. The consequences do not become noticeable immediately. But over time, they manifest themselves, in particular, in the dynamics of business margins, which begin to change more predictably.

5.2. Formation of the AI economy of business margins

The introduction of AI agents changes the cost structure of the enterprise, shifting the emphasis from variable personnel costs to relatively stable investments in technology. If in the traditional model, the main share of costs is formed by operating costs for customer service, then in the conditions of using AI agents, costs are redistributed towards the development, implementation and support of digital solutions. efficiency due to the growth of labor productivity [11].

What is the key effect? You can scale without increasing costs. This changes the expansion logic. The AI agents you deploy can serve an increasing number of customers without proportionally increasing the number of staff. Your costs don't increase the same way (no wonder it's called "hyperautomation"). Your marginal costs fall, and resource efficiency increases. A study by the Boston Consulting Group shows how digital transformation is already beginning to change roles and functions within the enterprise in deep, tangible ways. Dependence on the human factor decreases, and the productivity of business processes, on the contrary, increases [20].

At the same time, effective management of marketing and operational processes, supported by analytical tools, provides a direct impact on the financial results of the enterprise [16].

To illustrate changes in the cost structure, typical ratios before and after the implementation of AI agents based on empirical studies are summarized.

Table 2. Cost structure before and after the implementation of AI agents

Expense item	Before the introduction of AI	After the implementation of AI
Personnel costs	The Dominant Part (Main)	Decrease in proportion (moderate)
Technology costs	Supporting role	share growth
Request processing costs	directly proportional to the volume	Reduction of marginal costs

Source: Systematized by the authors on the basis of generalization of empirical studies [11; 16; 20].

Reducing the share of personnel costs and optimizing the cost of processing requests creates prerequisites for increasing margins. At the same time, the growth of technology costs is of an investment nature and does not increase in proportion to the volume of service, which provides a long-term economic effect.

It is important that as a result of such a transformation, the cost ratio itself changes. The structure no longer looks the same as before. The share of variable costs is gradually decreasing, while investments in technology are taking on the character of fixed, but at the same time, scalable costs. This is a different type of expense. As a result, the effect of operating leverage is formed. It is not always immediately noticeable. But with the growth of service volumes, its impact intensifies and begins to be noticeably reflected in the financial result.

The financial result of such changes can be formalized through the margin indicator:

$$Margin = \frac{Revenue - Costs}{Revenue}, (1)$$

With the introduction of AI agents, the reduction of variable costs translates into a decrease in costs for each item of expenditure in income. The effect is quite obvious. If the amount of revenue stays in place or grows, it leads to an increase in the margins of the business over time. Changes accumulate. Thus, the margin economy formed on the basis of artificial intelligence is not generated by a single factor. It is created at the intersection of several processes. One is productivity gains, another is cost optimization, and the third is the reinforcement that occurs when these processes occur at scale. Their combination leads to a more stable growth of the financial productivity of the enterprise.

5.3. Formation of the client's LTV in the conditions of AI automation

The introduction of AI agents into customer service affects the long-term value of the customer due to changes in behavioural parameters, primarily the retention rate. Increasing the speed of response and personalization of interaction contributes to increased customer satisfaction, which is directly related to repeat purchases and the duration of interaction with the brand [1; 7; 10].

The key mechanism for the formation of LTV is the relationship between retention rate and frequency of interaction. Even a moderate increase in retention rates leads to a disproportionate increase in LTV as the overall duration of the customer lifecycle increases [3]. The use of AI agents enhances this effect due to systemic personalization and continuity of interaction within CRM systems [12].

The additional application of machine learning models allows predicting LTV based on customer behavioral data, which increases the accuracy of management decisions and ensures the transition from reactive to proactive management of the customer base [6].

The formalization of LTV can be represented as follows:

$$LTV = ARPU \times RR \times CL, (2)$$

ARPU (Average Revenue Per User) is the average revenue per user for a certain period
RR (Retention Rate) — customer retention rate

CL (Customer Lifetime) is the expected duration of the customer's "life cycle."

To summarize the impact of AI agents on key components of LTV, a table is provided.

Table 3. The Impact of AI Agents on LTV Components

Indicator	**Before the introduction of AI**	**After the implementation of AI**
ARPU	relatively stable level	moderate growth
Retention rate	Basic level	Growth
Frequency of interaction	Intermediate level	Increase
Life cycle duration	limited	Elongation

Source: Summarized by the authors on the basis of [3; 6; 7; 10; 12].

As follows from the results in Table 3, the long-term value of the client is formed not as an isolated indicator, but as an integrated result of changes in several interrelated parameters. First of all, there is an increase in the level of customer retention, which confirms the conclusions of N. Ali et al. [3], according to which even moderate changes in retention rate can significantly affect the overall economic value of the customer base. At the same time, the frequency of interaction increases and the duration of the customer life cycle is extended, which is consistent with the results of Y. Chen and K. Hardcastle [7; 10], which emphasize the role of personalization and service quality in shaping stable customer behaviour. Thus, the changes recorded in the table are cumulative in nature and are manifested through the gradual strengthening of the relationship between behavioural and financial indicators.

5.4. Integrated financial model for the implementation of AI agents

The results obtained allow us to proceed to generalization of the financial effect of the introduction of AI agents within the framework of an integrated approach. It is important that the growth of LTV occurs in parallel with the optimization of operating costs, which is confirmed by the studies of B. Y. Kassa and M. Prodanchuk [11; 16]. This indicates the presence of a double mechanism for the formation of a financial result: on the one hand, through a decrease in costs, and on the other hand, through an increase in income, due to an increase in the long-term value of the client. Such interaction of operational and behavioural factors determines the logic of building an integrated financial model for the introduction of AI agents:

AI agents ⇒ : operational efficiency, ⇒ cost reduction⇒, margin growth, ⇒ increase in LTV ⇒ ROI.

Increased productivity and reduced cost of processing requests generate cost savings, while improved customer experience provides revenue growth due to increased LTV. Such integration of operational and behavioral factors creates a complex effect that determines the financial efficiency of AI implementation [11; 16].

The economic feasibility of implementing AI agents can be assessed through the ROI indicator:

$$ROI = \frac{(\Delta Revenue + \Delta Cost\ Savings) - Investment}{Investment}, \quad (3)$$

where *ΔRevenue* reflects revenue growth due to increased LTV, and *ΔCost Savings* reflects cost savings due to automation.

Fig. 2. Integrated Financial Model of AI Agent Impact

Source: Developed by the authors based on [3; 5; 11; 16].

The above model highlights the fact that the ROI obtained from the use of AI agents is a combination of factors that are simultaneously shaped by cost reduction and increased revenue. This supports the idea that the financial model we build on operational performance should also take into account behavioral effects for customers, as confirmed by our experiments in other studies [10; 14].

5.5. Limitations and possible risks of the introduction of AI agents

Although the positive impact of AI agents on customer service has already been demonstrated, there are a number of limitations that can curb the growth of the economic effect. One problem is the phenomenon of reluctance to automate, such as the tendency of customers to fear poor automated interactions. Yao et al. [18] argue that with the same response quality, users will still prefer human interactions in most complex or special cases, imposing limitations on fully automating the service. It is necessary to take into account the behavioural reactions of users when implementing AI agents.

The second important aspect is the risk of a decrease in the quality of service, as well as the socio-psychological features of human interaction with artificial intelligence. This issue has already been thoroughly considered in a study by Pitardi et al. [15]. It deserves attention. Zhao and Wu note that AI agents work well with standard queries. But in more difficult situations, everything looks different. Errors, repeated answers, or an inaccurate understanding of the query appear. This is felt by the user. In some cases, such failures reduce customer satisfaction and affect brand perception. The reaction is not always immediately noticeable. But it accumulates. Accordingly, automation alone does not guarantee an increase in the quality of service. Without proper adjustment of models and constant monitoring of their work, the result may be the opposite [19].

Of particular importance is the balance between the use of artificial intelligence and human participation in the service process. This issue cannot be ignored, since the final quality of the service largely depends on the configuration of the AI-human interaction. S. Rana et al. substantiate that the most effective is the hybrid model, in which AI agents process routine requests, while complex and non-standard situations are transferred to operators [17]. This approach is consistent with the results of Y. Chen, which emphasize that the perception of customer experience depends not only on the speed of service, but also on the level of personalization and quality of interaction [7]. This configuration combines the benefits of automation – speed and scalability – with the flexibility, adaptability, and empathy inherent in human involvement. This combination allows you to maintain a high level of customer experience even in complex interaction scenarios.

It is also important to consider the variability of the effect of AI adoption depending on the context. As shown by Enholm et al. [8], as well as Zoppelletto et al. [20], the effectiveness of using AI agents differs depending on the industry, product complexity, type of customer interaction, and the company's level of digital maturity. In standardized processes, the effect of automation is more pronounced, while in services with a high proportion of individualized requests, it may be limited.

6. Conclusions

Thus, the use of AI agents in customer service changes the very logic of the operating model of the business. It no longer looks so dependent on resources. The logic is changing. There is a sense of scalability that was previously unattainable. At the centre of this transformation is the automation of interactions, more accurate cost management, and incremental impact on customer behaviour. This is what determines the result. Automation of routine processes increases service productivity, reduces response time and reduces the workload on staff, freeing up resources for more complex tasks. As a result, there are conditions for expanding activities without a noticeable increase in costs. This is a different model. Gradually, a new margin economy is formed, where a decrease in variable costs is combined with an increase in productivity and financial returns.

The key conclusion of the study is related to the identification of a causal relationship between service automation and long-term customer value. It doesn't happen instantly. The effect accumulates. Increasing the level of personalization, speed, and availability of interaction is gradually changing the perception of the service. Customers feel it. Satisfaction increases along with the quality of interaction, and this, in turn, affects financial performance due to repeat appeals and stability of demand. Over time, these changes translate into an increase in the long-term value of the customer base. As a result, the financial effect of the introduction of artificial intelligence agents is manifested not only through cost reductions. No less important is the gradual growth of income in the long term.

The scientific novelty of this work lies in the proposed integrated financial model. It looks like an attempt to assemble disparate parts into one. The model combines operational parameters – efficiency and cost – with behavioural characteristics such as customer satisfaction and retention. It is this combination that matters. It allows you to more accurately see the financial effect of using artificial intelligence agents. The model does not just record indicators. In particular, how service automation is gradually reflected in the margin of the business and the long-term value of the client. After all, previous studies have tended to look at these effects separately, focusing either on costs or customer behaviour. Here, they are reduced to one logic, which looks more holistic and closer to real practice

Separately, it is worth noting that the effectiveness of using artificial intelligence agents is not universal. It all depends on the conditions. The specifics of the business model, the types of client scenarios, especially complex ones, and the level of digital maturity of the enterprise are important. Certain restrictions have also been identified. Some customers do not accept automated interaction. In difficult situations, the quality of service may decrease. A complete replacement of human participation looks unlikely so far. That is why a more justified approach is the use of hybrid models, where technology complements a person and does not displace them.

The practical benefit of the study lies in the ability to apply this model to justify decisions on the implementation of artificial intelligence in service processes. It allows you to assess not only the economic effect of such decisions, but also their impact on long-term relationships with customers. However, the work does not end there. Further study of the topic requires empirical verification of the model in different sectors and a deeper analysis of the relationship between customer behaviour and the financial dynamics of the enterprise.

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